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Human Capital Data: Evidence and Suggestions from Italian Time Series (1881-1993)

Renato Giannetti and Margherita Velucchi *

Abstract: The controversial results obtained by introducing human capital in the traditional regression growth pushed the researchers to search in different directions: refining the measurement of human capital, adding measures of quality of schooling, etc. The paper copes with the econometric side of the regression of human capital on GDP per capita investigating the characteristics of the time series representing human capital. The usual regression techniques assume a linear relationship between the dependent variable and the independent ones, and the independent and identical distribution hypothesis on residuals. The paper shows that this is not the case, for both the conditions, in the series of secondary school enrollment rate to the population of the same age in Italy from 1881 to 1991. Therefore using standard econometric techniques to investigate the role of human capital on GDP is incorrect. As an alternative approach, the paper proposes a kernel regression which is a non parametric method by which observations are weighted according to a particular function. The results are comfortable. The regression finds a non linear relationship between economic growth and human capital, showing that human capital is significative for Italian GDP growth since 1965, when the Reform of Secondary School (1962) displayed its effects. The paper extends this method to the traditional factors (K;L) and finds a similar relationship and timing for labour, while only capital time series show a linear relationship as is usually presumed in the standard production function.

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"Where all that education has gone ?"
(Lance Pritchett)

Introduction

The Cobb Douglas production function is the most widely used model to measure the influence of education on growth. For example, consider a linearized Cobb Douglas function :

$$\ln GDP = \alpha \ln K + \beta \ln L + \gamma \ln H ,$$

where GDP is the gross national product, K is the physical capital stock, L is represented by the units of labor and H represents the stock of holders of (usually) a secondary school diploma; the effect of H on GDP is generally evaluated estimating a classical cross section model of regression (Barro, 1991) to compare several countries or a linear regression model, using time series, to measure a single country evolution. This approach is commonly used (Solow, Mankiew, Romer, 1992) but it is based on hypotheses which should be accepted with care; if and only if we are sure the variables we are treating have these characteristics we can apply a classical regression model and derive consistent conclusions. These hypotheses are: the relationship between regressors and dependent variable is linear; any relationship is absent between the regressors and residuals; the residuals are independent and identically distributed. If one of these assumptions cannot be taken for granted, the classical regression model cannot be used.

This paper analyses the inner structure of the variable usually used to measure education (\log of the ratio of secondary school enrolled to population in the same age, $\ln R_t$) to test the coherence of the assumption on the residuals of the series (i.i.d. hypothesis) and to emphasize the relevance of internal dynamics knowledge before any treatment on the series. We use the yearly series of the variable above for Italy in the period 1881-1993 (Checchi, 1997) and we treat the variable both with the Nelson and Plosser DS approach and with the segmented trend using structural breaks. These approaches need the i.i.d. assumption on residuals even if this hypothesis is often rejected for many macro-economic time series (Rappoport and Reichlin, 1987, Perron, 1989, Caselli and Marinelli, 1994). Furthermore, the standard Dickey-Fuller Test cannot be used to distinguish a random walk from non-linear dynamics. For example, in presence of a broken trend or non-linear dynamics the Dickey-Fuller test do not allow to reject correctly the random walk hypothesis even when we know a priori that the time series is generated by a deterministic process (Bevilacqua and Van Zon, 2001). If we want to discriminate stochastic processes from the deterministic ones we should use non parametric tests. We show that the inter-

nal dynamics of the residuals of the series are not distributed as white noise (the i.i.d. assumption does not hold) and, consequently, we suggest an alternative representation of the relationship between education and growth using a kernel regression approach.

The Unit Root Approach

Nelson and Plosser in 1982 investigated the nature of macroeconomic time series analysing whether time series could be better characterized as stationary fluctuations around a deterministic trend, as the real business cycle theory states, or as non stationary processes that have no tendency to return to a deterministic path; they have shown that irregularity in macroeconomic time series could be simply explained by the introduction of random shocks with persistent effects. Their paper raised a lively debate among economists on macroeconomic time series, because disputed the usual representation of the dynamics of economic time series as linearly deterministic and stationary. They started their analysis with the standard decomposition of real variables into a secular or growth component and a cyclical component, where the secular component concerned real factors as population growth or technical change and the cyclical component was assumed to be transitory (stationary) and dissipate over time; because of the assumptions on the cyclical component, any long-run variation was attributed to the secular component. They concluded that the models based on purely transitory fluctuations were not useful in explaining the variations in macroeconomic time series because of the representation of non stationarity in time series. They considered two classes of non stationary processes: the first one (*TS*) consists of those that can be expressed as a deterministic function of time (trend) plus a stationary, stochastic process with mean zero, the second one (*DS*) is the class of the processes which are stationary in first, second or higher order differences. Assuming the *DS* class is appropriate to describe macroeconomic time series dynamics means that any movement in short term will have some effects in long term positions, while this effect is much more reduced with *TS* processes.

We turn to the empirical analysis of the time series of Italian education represented by the annual rate of secondary schooling enrolment to population in the same age (1881-1994). We start describing R using the sample autocorrelation function, which decays very slowly increasing lag (Table 1). This is coherent with the random walk representation of the sample autocorrelation. Sample autocorrelations of first differences are presented in Table 2 and stress a single, significant value of autocorrelation at lag 1; this is coherent with a *DS* representation (*first order MA process*) and not with a *TS* representation. To strengthen this result we present in Table 3 the sample autocorrelations of the deviations from fitted trend lines in which data are residuals from linear

squares regression of the logs of the series on time; the pattern is quite similar to that of sample autocorrelation in first differences. All the previous results on sample autocorrelations are very important to fix the maximum number of significant lags (k) in the series in order to carry out a formal Augmented Dickey Fuller test. The *ADF* tests estimates a regression of the form:

$$z_t = \mu + \gamma + \rho z_{t-1} + \sum_{j=1}^k \rho_j (z_t - z_{t-j}) + u_t,$$

where $j: 1, 2, \dots, k$ are the significant lags and $u_t \sim i.i.d(0, \sigma^2)$. The null hypothesis in *ADF* is $\rho = 1$ and if we accept it, we assume the existence of a unit root in the time series and so the consistency of a *DS* representation. The *ADF* results (with the constant and the drift) are reported in Table 4: they show the existence of an unit root, i.e. the evidence confirms the consistency of a *DS* representation of non stationary time series of education.

Our previous analysis suggests that secondary schooling rate of enrolment has not a deterministic time trends, but has the stochastic trends characteristic of the *DS* class process. The decomposition of the series suggests the cyclical component is transitory and the non stationarity can be attributed to the secular or growth component, i.e. shocks cumulate and are not immediately absorbed by the time series. The estimated values are presented in table 5 and graphically the model is represented in figure 2.

The Segmented Trend Approach

Since the Nelson and Plosser paper appeared, many empirical studies concluded that macroeconomic time series have unit roots and belong to the *DS* class. Contrary to this view, Rappoport and Reichlin (1987, 1989) and Perron (1987) suggested the *TS* class is not a correct alternative to understand which is the real nature of time series; they proposed to introduce infrequent breaks to segment the trend of a *TS* process showing the Dickey Fuller test, in presence of a broken trend, does not allow to accept or correctly reject the null hypothesis (the unit root existence). As a result, the empirical success of *DS* models may have occurred because the alternative did not allow for sufficient flexibility in the trend, i.e. it was underparameterized. Rappoport and Reichlin proposed a segmented trend representation of time series, introducing a priori information (*structural breaks*) in the *TS* class. This approach, although suggestive, can be implemented only if we have a large information of the series we are treating and therefore it is not much interesting in forecasting. In the spirit of Box and Tiao (1975), they introduced in a standard *TS* process two types of variables: the *pulse* and the *step* variables. The *pulse* variables take value one in a particular moment and zero otherwise; they are introduced to eliminate the effect of a particular event (they capture a change in the slope of the trend) while the *step* variables take value one for a particular interval of

values and zero otherwise and they are deemed to capture a permanent change in the value of intercept in time.

The choice of a break point in time series is quite ambiguous and it has been criticized (Hausman, 2001). In Italian education time series we have checked two structural breaks and we have tested them with a Forecast and Breakpoint Chow Test.¹ The first of the two breaks is in 1925, the second one in 1944; these two breaks are self evident and can be easily explained but, in general, changing slope and trend are not so clear and the risk is to attribute importance to an irrelevant event or viceversa and deduce non sense conclusions. In the Italian secondary schooling rate of enrolment series, the first break is due to the schooling system Reform of 1923 (due to Giovanni Gentile), while the second one is due to the collapse of the Italian institutions, including the school system, after the Armistice on September 8 1943 (Cives, 1990).

In Table 6 we present the results of Forecast Chow test for the major of the two breaks (1943) while the results for 1925 are derived by a Breakpoint Chow Test. These tests for parameter constancy are based on the series of the residuals of the Recursive Least Squares estimation, $\{RSS_t\}$, of the function $\ln R_t = \alpha + \beta t + \gamma \ln R_{t-1} + \varepsilon_t$; where $\ln R_t$ represents the logs of secondary schooling rate of enrolment, t is the time trend, α is the constant term and β and γ are asserted to be constant, $E(\ln R_t, \varepsilon_t) = 0, \forall t$ and $E(\varepsilon_t, \varepsilon_s) = \sigma^2$ if $t = s$ and zero otherwise. Looking at Table 5, there is a significant and permanent jump in 1943 in the sequence of $\{RSS_t\}$ confirming this date as the strongest breakpoint. In relation to the first one (1925), we cannot simply repeat the previous procedure given the presence of the 1943 break which could hide other smaller breaks; we reduced the sample (1881-1940) and use the Breakpoint Chow test. Therefore the results in Table 6, show even the first break (1925) is significant. We proceeded to test the trend stationary model with breakpoints. Let $\{\ln \hat{R}_t\}$ be the residuals from a regression of $\ln R_t$ on a constant, a time trend, a dummy variable representing the change in the slope and another dummy variable representing the change in the level of the series. Let $\hat{\beta}$ be the least squares estimate of β in the following regression: $\ln \hat{R}_t = \hat{\beta} \ln \hat{R}_{t-1} + e_t, t : 1, 2, \dots, T$. The series $\{\ln \hat{R}_t\}$ corresponds to the residuals of the following regression by using *OLS*:

$$\ln R_t = \alpha_0 + \alpha_1 t + \sum_i (\beta + \gamma_i t) d_i^s + \sum_j \delta_j d_j^p + \zeta_t$$

$$\zeta_t = \theta^{-1}(L)\Theta(L)u_t = \ln \hat{R}_t, u_t \sim \text{i.i.d.}(0, \sigma^2)$$

where $t : 1, 2, \dots, T$; $i : 1, 2, 3$; $j : 1924, 1925, 1926, 1927, 1941, 1942, 1943, 1944, 1945, 1946$ $d_l^k, l : i, j$ and $k : s, p$ are the *step* and *pulse* variables used to

¹ The procedures used to test the existence of different amplitude breaks are differed to esclude the possibility that the bigger could hide the smaller. To verify the existence of smaller breaks we have to reduce the sample size and test them through the Breakpoint Chow Test.

eliminate the effects of the events on the slope and on the intercept, $\theta(L)$ and $\Theta(L)$ are polynomials in the lag operator which have all roots outside the unit circle. All the parameters in Table 7 are statistically significant except for 1940 and 1941 while the goodness of fit is 0.979. As we expected, the residuals are not a white noise process because they include the lagged significant value of the dependent variable, which is not introduced in the model (DW statistic is near zero and sample autocorrelation decay very slowly). The graphic representation is reported in Figure 3.

The Non-linear Approach

As already noted, the previous two approaches are based on the i.i.d. assumption on residuals - which is a necessary assumption for all linear models- and their explanation of the dynamics of time series is obviously influenced by this assumption. Moreover, the unit root and the segmented trend approaches represent time series evolution as a linear phenomenon which can deviate from the trend because of the presence of an exogenous shock or of a cumulate of exogenous shocks. These representations do not consider the nature of the shock but its persistency. Moreover they do not pay attention to the inner structure of the residuals (fixing they're *i.i.d.*), therefore they assume time series path is substantially linear, obscuring existent non linearities which may be endogenized in non linear models.

We suggest an approach which criticizes both the unit root and the segmented trend representation, rejecting the hypothesis the series are generated uniquely by a linear stochastic process. Bevilacqua and Van Zon (2001) propose a dynamic and non linear explanation to describe and forecast the evolution of a system: i. e. a non linear metric method based on chaos theory to identify structures that endogenously generate fluctuations in macroeconomic time series.

In our empirical work on Italian education series we concentrate on residuals of stationary time series, so we consider still relevant the unit root explanation but, starting from this, we relax the assumption on independent and identical distributed residuals to test the existence of non linearities. The aim is to identify the process that generates the non stationarity without stating *ex-ante* that non stationarity is a direct consequence of a stochastic process. We check the inner structure in residual showing that it is very different from a white noise, therefore residuals are not random at all and they are not exogenous but a result of endogenous interactions.

We have already mentioned the *ADF* difficulty in distinguishing a broken trend from non linear dynamics even if *a priori* is well known that the process is deterministic; we use a non parametric test (*BDS* test by Brock, Dechert, Scheinkman) which is much more sensitive to detect non linearities, although it

ensures good power properties only for large sample sizes. We then use Ruelle Plot to uncover, from a qualitative point of view, the hidden structures of the secondary schooling series. Ruelle Plot is the "graphical description" of the Euclidian distances between the realizations of the stationary series; each point in the plane is the representation of this distance and the colour is its visual image. For each bundle of the stationary time series $D(\ln R_t)$ represented by $(D(\ln R_{t-i}); D(\ln R_{t-j})), t: 1, 2, \dots, T; i, j: 1, 2, \dots, m$ where m is the embedding dimension,² the Euclidian distance has been evaluated and to each distance has been associated a colour in the spectrum: white if the distance is zero $D(\ln R_{t-i}) = D(\ln R_{t-j})$ and black for the maximum distance, all the grey tones for distances in between. Obviously the 45 degree line $D(\ln R_{t-i}) = D(\ln R_{t-j})$ is a white line dividing the space in two parts.

We present the Italian secondary schooling series representation in Figure 4 and compare it with a white noise process in Figure 5. The secondary schooling rate has a unit root and it can be characterized by two structural break, but it shows structured dynamics in the residuals. In particular, from the previous plot, we can detect easily that the years characterized by irregular dynamics are exactly those we have introduced as structural breaks. They are represented by those lines marked with light grey (1925) and dark grey (1944). We proceed to ascertain quantitatively whether the time series is generated by a non linear deterministic process and we apply the BDS test; we test the null hypothesis of independence and identical distributed residuals versus an alternative one which considers any possible different relationship (linear, non linear, chaotic). Because of the small size in time series, we treat it with a bootstrap analysis which evaluates the BDS test both for the data as they are in the sample and for each randomisation of it. For each repetition, BDS is recalculated for the randomly drawn data, then it is compared to that obtained from the original data. When all the repetitions are complete, the final value of the bootstrapped p-value results from dividing the lesser of the number of repetitions above or below the original statistic by the total number of repetitions, then multiplying by two (to account for the two tails). The results (Table 8) confirm that the null hypothesis is strongly rejected.

We conclude that this process is not driven by chance; residuals in secondary schooling series show a structure that does not come from a linear stochastic process and therefore a non linear explanation is needed to understand the temporal causality of events.

² m gives the minimum dimension of the vector used to calculate the euclidian distance. The method of choosing the minimum embedding dimension of a one-dimensional time series is the False Nearest Neighbors. This method finds the nearest neighbor of every point in a given dimension, then checks to see if these points are still close neighbors in one higher dimension. The percentage of False Nearest Neighbors should drop to zero when the appropriate embedding dimension has been reached.

A Proposal

The analysis above shows some interesting properties of the series. Briefly sketching them: Italian secondary schooling series is a non stationary time series which presents a unit root; it can be well described introducing a priori information on events which break the trend of the series in particular moments, but the residuals of the series are not *i.i.d.* as assumed by both the Nelson Plosser and Rappoport - Reichlin approaches. In the light of these remarks, we cannot use the classical regression model which builds up on these assumption to evaluate the influence of education on growth.

In the present paragraph we propose, firstly, to evaluate the effect of Italian education on growth using a local polynomial kernel regressions of R on Pil .³ Kernel regression is a non parametric method⁴ by which observations are weighted according to a particular function, the so called *kernel* function. Local polynomial kernel regressions fit Pil , at each value r , which represents any possible realization of the variable R , by choosing the parameters β to minimize the weighted sum of squared residuals:

$$m(r) = \sum_{t=1}^T Pil_t - \beta_0 - \beta_1(r - R_t) - \beta_2(r - R_t)^2 - \dots - \beta_k(r - R_t)^k)^2 N\left(\frac{r - R_t}{h}\right)$$

where T is the number of observations, h is the bandwidth (or smoothing parameter), and N is a kernel function that integrates to one. Note that a kernel regression reduces to a linear estimation function when $N[(r - R_t)/h]$ is a constant, i.e., when the relationship between the variables is linear.

In figure 5 we present the graph which displays fits of local polynomial kernel regressions of R on Pil ; the relation between education and growth is well estimated by the *Epanechnikov* kernel function:

$$N\left(\frac{r - R_t}{h}\right) = \frac{3}{4} \left(1 - \left(\frac{r - R_t}{h}\right)^2\right) I\left(\left|\frac{r - R_t}{h}\right| \leq 1\right)$$

where I is the *indicator function* which takes value one when the argument is lower or equal to one and zero otherwise and the bandwidth is $h = 0.02$. The graphical representation shows a non linear effect of education on growth: low values of R do not affect significantly growth, but its effect becomes evident (the slope of the curve is increasing) starting from $R = 0.2$ which is compatible with the value in the second part of the sixties.

³ We neglect the transformed variables used to linearize the Cobb Douglas function; we use R and Pil (instead of their log transformation) their relationship is non linear. Logaritms are no more useful because we don't have to linearize any expression before estimating it.

⁴ Note that nonparametric methods do not request any assumption either on the nature of the relationships between variables or on residuals distribution.

Secondly, we extend the method to consider all the variables of the standard production function, sketching them with a parallel representation.⁵ In figure 6, 7 and 8 we present the graphical representation of the variables of enrolment (R), labour (L) and capital (K) on growth using the previous kernel function with the same bandwidth (Rossi, Sorgato, Toniolo, 1993). It is evident the non linear relationship between labour and growth while a substantial linearity concerns the capital-growth relationship. L shows a pattern quite similar to R ; its effect on growth is not particularly strong for low values of the variable, but it becomes much more evident starting from the second part of the sixties: its relation with Pil is non linear. On the contrary, the effect of capital K on growth is substantially linear and it can be well detected also with a linear regression analysis.

Figure 9 resumes the behaviour of all the variables in a parallel representation; the first graph represents the fit of L , K , R on the values of Pil (the first graph is the relation of Pil with itself) while all the other graphs are the single cross relations between the same variables. In other terms, the first column of graphs shows the relation between Pil and Pil , L , K , R respectively, the second column shows the relation between L and Pil , L , K , R and so on; obviously, the relation of a variable with itself is a 45 degree line. If the relations between Pil and the dependent variables would be linear their graphical representation should be a line. Using this representation, we can observe that Italian education and labour patterns are not significant for low values of the variables: their effect becomes evident starting from the second part of the sixties, probably as an effect of the school system reform of 1963 which made compulsory a three years course after primary school, so strongly increasing the number of the secondary enrolled students. The relationship between capital and growth, instead, is clearly linear, as in standard analysis.

Conclusion

The controversial results obtained by introducing human capital in the traditional regression growth pushed the researchers to search in different directions: refining the measurement of human capital, adding measures of quality of schooling, etc. We cope here with the econometric side of the regression of human capital on GDP per capita investigating the characteristics of the time series representing human capital. The usual regression techniques assume a linear relationship between the dependent variable and the independent ones and the independency and identical distribution of residuals. We show that this

⁵ In this case we have reduced the sample to the period 1951-1991 because of the lack in labour and capital data.

is not the case, for both the conditions, in the series of secondary school enrolment rate to the population of the same age in Italy from 1881 to 1991. Therefore using standard econometric techniques to investigate the role of human capital on *GDP* is incorrect. We propose here an approach based on kernel regression which is a non parametric method by which observations are weighted according to a particular function. The results that we obtain are comfortable. We find a non linear relationship between economic growth and human capital, which shows that human capital is significative for Italian GDP growth since 1965, when the Reform of Secondary School (1962) displayed its effects. We extend this method to the traditional factors (K ; L) and find a similar relationship and timing for labour, while only capital time series shows a linear relationship as is usually presumed in the standard production function.

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Figures and Tables

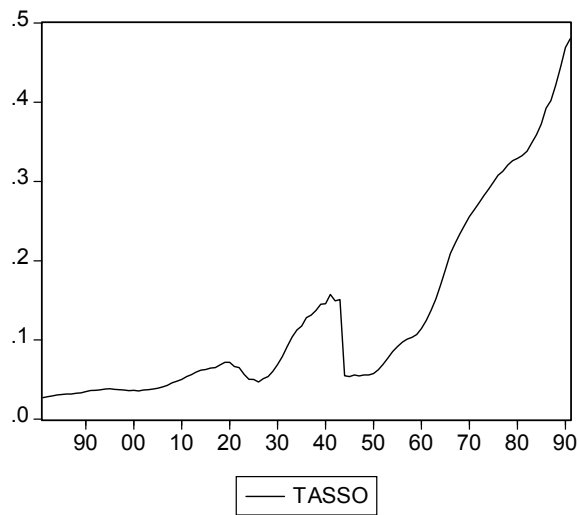


Figure 1: Enrollment rate on population of the same age

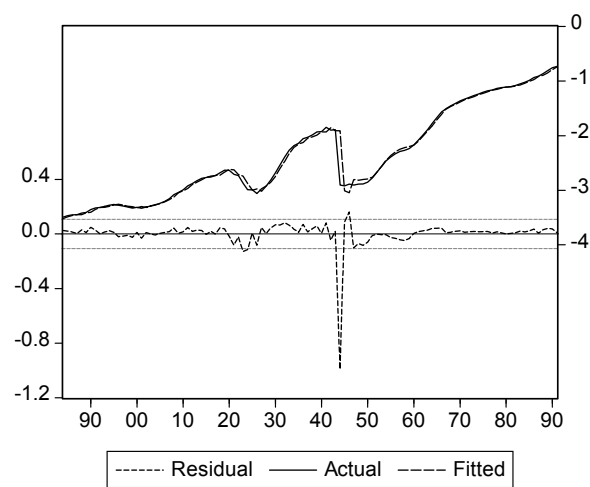


Figure 2: Unit Root representation

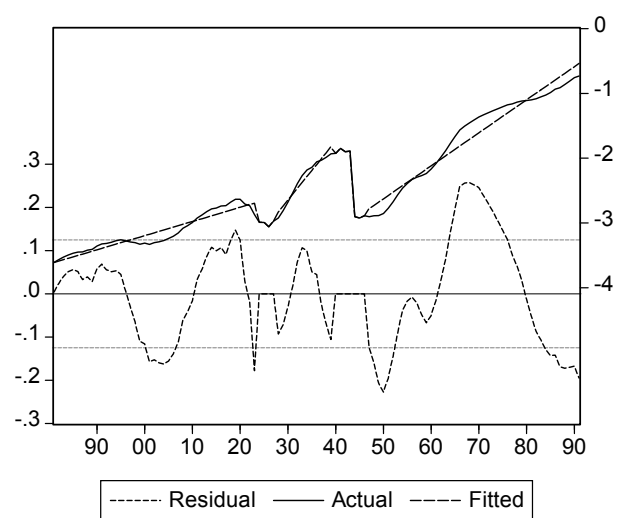


Figure 3: Segmented Trend representation

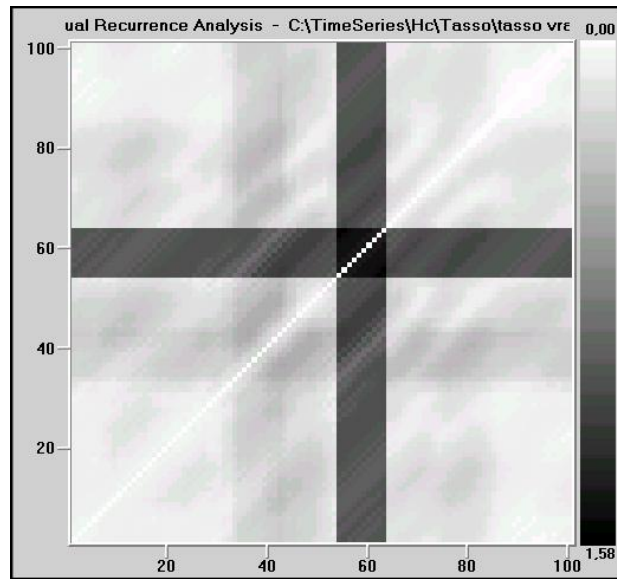


Figure 4: Recurrence Plot of the Enrollment Rate

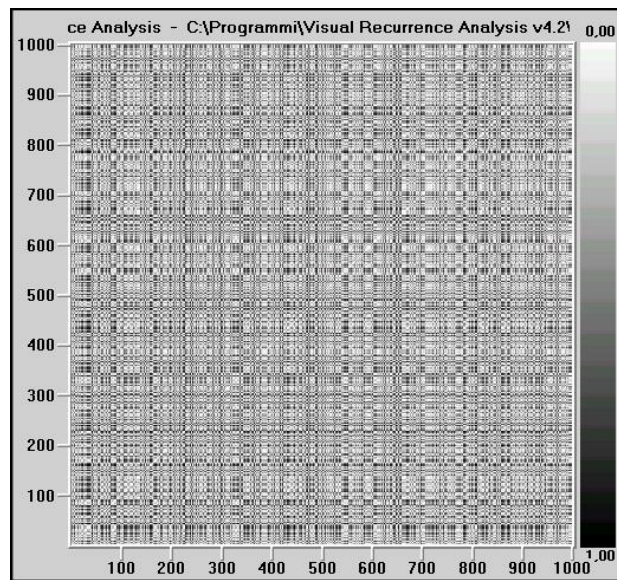


Figure 5: Recurrence plot of a white noise process

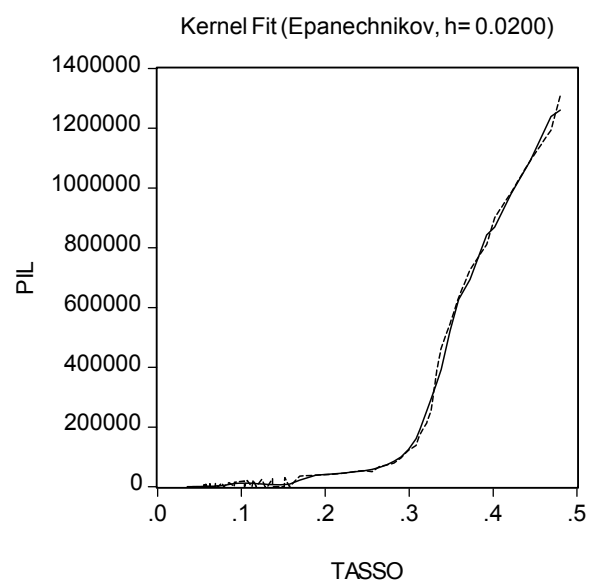


Figure 6: Kernel Fit of the Enrollment Rate on Growth

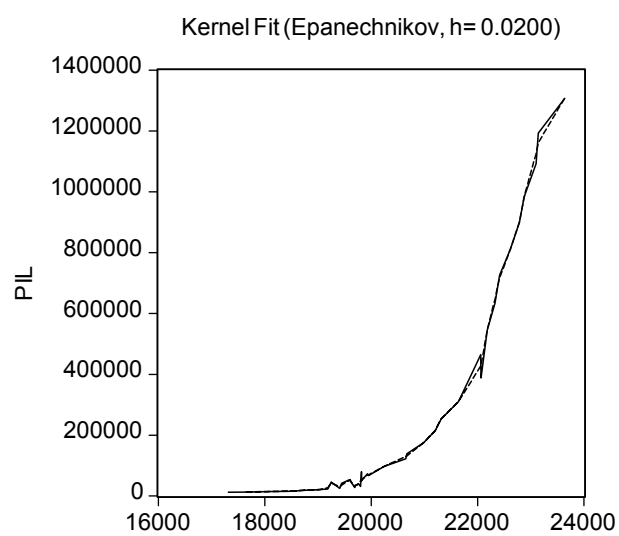


Figure 7: Kernel Fit of Labour on Growth

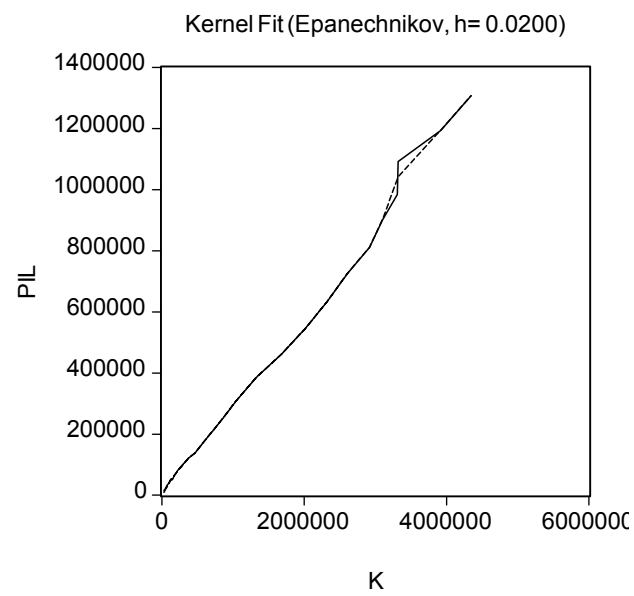


Figure 8: Kernel Fit of Capital on Growth

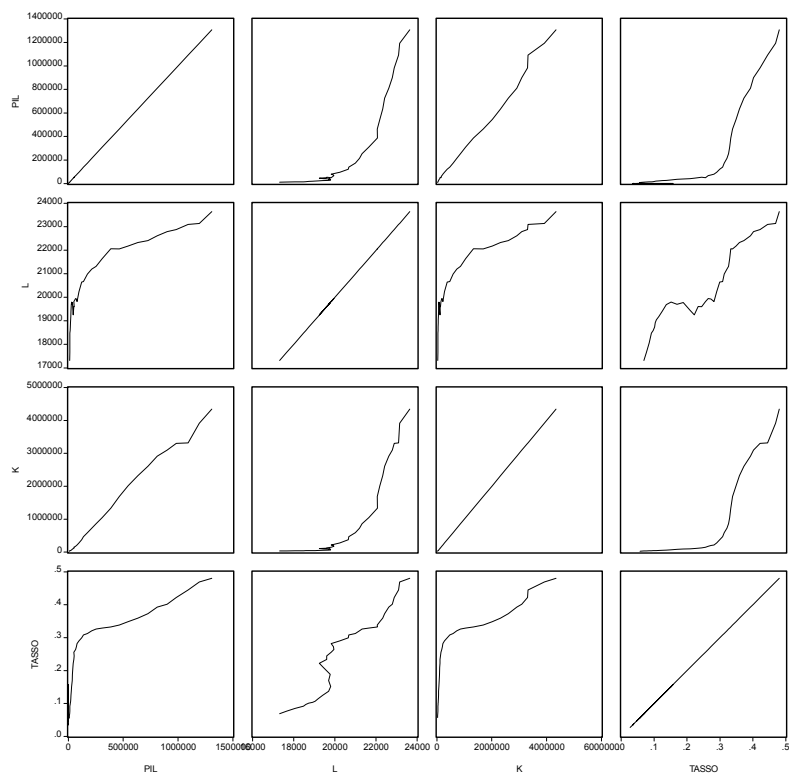


Figure 9: Parallel Representation of Labour, Capital and Education on Growth